Software requirements specification Document Workout assistent

Poula Moheb, Ahmed Mohamed Hassan, Abdelrahman Khashaba, Ahmed Nagy

Thursday, 6th of February 2020

1 Introduction

1.1 Purpose of this Document

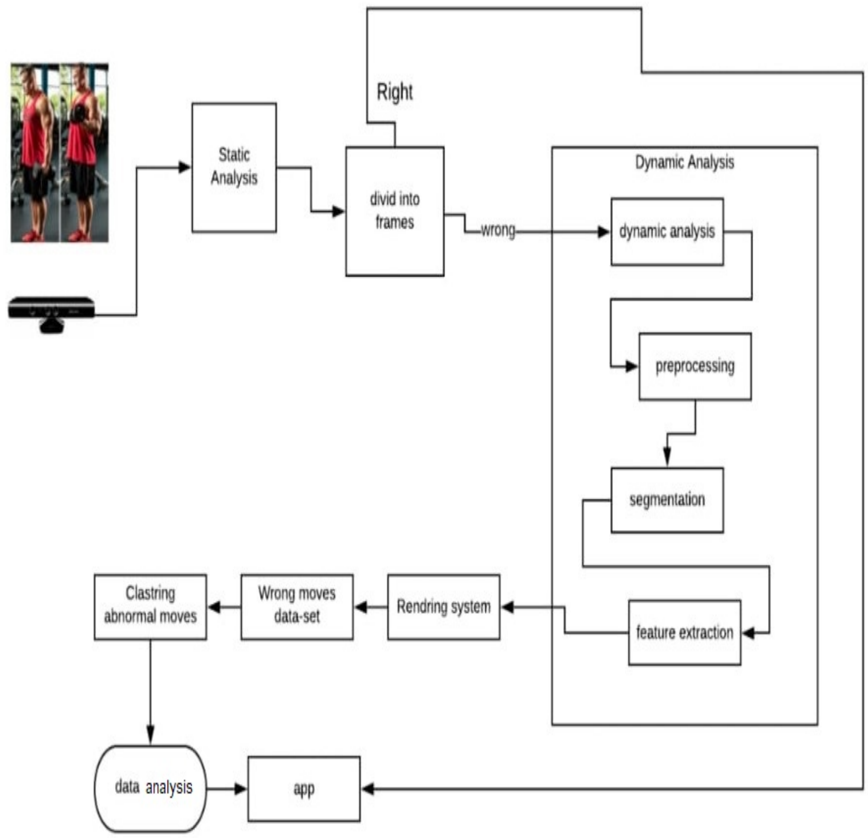
The purpose of this system is to detect the movement which will catch by the Kinect camera which will be analyzed to get the dimensions of x y z and the joints. System will be trained at first to make the classifier more accurate then there will be some testing subject to test whether the system is accurate or not then test with a real data by which will classify the movement into right and wrong then correct the wrong on real time. The Kinect could capture 30 frames for each 22 joints per second. Better than sensors because sensors are expansive need a lot of them just to detect one joint. The sensors are not accurate as the Kinect and they need to be synchronized to work with each other.

1.2 Scope of this Document

The technique that we use is directed to help the people who are looking for the best way to train their body without fearing of injures and gaining the best body fit look. The system is very simple to access and use it. System will detect the body and track its motion. Preprocessing and joints extraction by static analysis, dividing the frames into right and wrong. The people who will use it will have guided instructions, how to do the exercise with the best way and correct for them any wrong move. All this will be available due to the 30 frames captured for every 22 joints per second. That will enhance the future of the training technique scope.

1.3 Overview

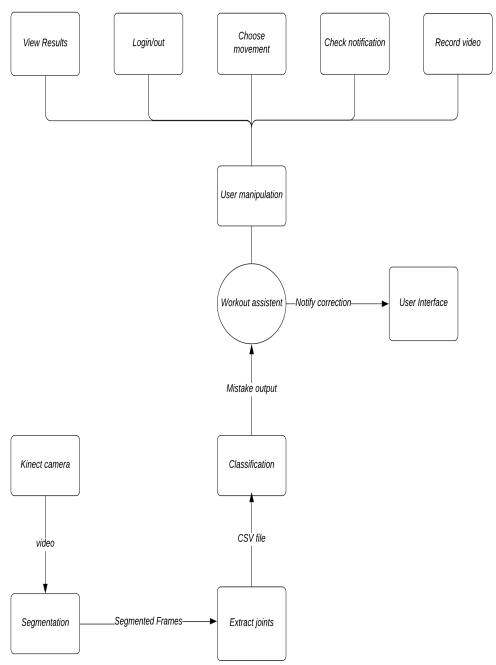
First, we will use the Kinect camera to detect the body of the person who is doing the exercise, 30 frames will be detected for the 22 joints per each second by the Kinect. The video will be taken by a Kinect camera The training phase is to increase the accuracy of the classier Using the SVM KNN DTW algorithms which will achieve a high accuracy The camera will analyze and extract the joints in the frames of the video . The algorithms will be used to train the classier on detecting and correcting the movements. Moreover, the rendering system will compare with the data set of the wrong movements, clustering abnormal movements.



view.jpeg

1.4 Business Context

Competitive bodybuilding is a weightlifting sport similar to power-lifting, strongman competition and Olympic weightlifting, which aims to increase muscle mass, symmetry, and body definition. Although data regarding rates of injury, overuse syndromes and pain during routine training is available for these other disciplines, it is rare for competitive bodybuilding. The aim of this study was to investigate rates of injury, pain during workouts and/or overuse syndromes, as well as the influence of particular intrinsic and external factors. Data was collected using questionnaires from 71 competitive and elite bodybuilders. The information included training routines and prior injuries. Participants were recruited from bodybuilding clubs in Germany. 45.1% of athletes reported symptoms while training. The overall injury rate was computed to be 0.12 injuries per bodybuilder per year (0.24 injuries per 1000h of bodybuilding).



2 General Description

2.1 Product Functions

2.1.1 Module 1:User Manipulation

LOGIN/OUT give access to the user to their accounts.
CHOOSE MOVEMENT chose one of three movement .
ADD/PLAY VIDEO
VIEW HISTORY DATA
CRUD DATASET add ,delete and edit

2.1.2 Module 2:Kinect camera

JOINT DATA capture joints positions and XYZ.
CSV store features into arrays

2.1.3 Module 3:Classification

KNN
SVM
FAST-DTW

2.2 Similar System Information

In [1] proposed: The great success of wearables and smartphone apps for provision of extensive physical workout instructions boosts a whole industry dealing with consumer oriented sensors and sports equipment. But with these opportunities there are also new challenges emerging. The unregulated distribution of instructions about ambitious exercises enables inexperienced users to undertake demanding workouts without professional supervision which may lead to sub-optimal training success or even serious injuries. They believe, that automated supervision and real-time feedback during a workout may help to solve these issues. Therefore they introduce four fundamental steps for complex human motion assessment and present SensX, a sensor-based architecture for monitoring, recording, and analyzing complex and multi-dimensional motion chains. They provide the results of our preliminary study encompassing 8 different body weight exercises, 20 participants, and more than 9,220 recorded exercise repetitions. Furthermore, insights into SensXs classification capabilities and the impact of specific sensor configurations onto the analysis process are given and the results of the preliminary study for activity recognition. The system consists of one central processing unit and four external sensors that track acceleration as well as rotation data. Moreover, it is able to track all four human extremities individually.

In [2] proposed: Creating the perfect wearable device to monitor muscle movement, heart rate and other tiny bio-signals without breaking the bank has inspired scientists to look for a simpler and more affordable tool.

Now, a team of researchers at UBC's Okanagan campus have developed a practical way to monitor and interpret human motion, in what may be the missing piece of the puzzle when it comes to wearable technology.

What started as research to create an ultra-stretchable sensor transformed into a sophisticated inter-disciplinary project resulting in a smart wearable device that is capable of sensing and understanding complex human motion, explains School of Engineering Professor Homayoun Najjaran. The sensor is made by infusing graphene nano-flakes (GNF) into a rubber-like adhesive pad. Najjaran says they then tested the durability of the tiny sensor by stretching it to see if it can maintain accuracy under strains of up to 350 per cent of its original state. The device went through more than 10,000 cycles of stretching and relaxing while maintaining its electrical stability.

In [3] proposed: An EMS-based Assistance System for Real-Time Running Style Correction Today, ambitioned amateur athletes often do not have access to professional coaching but still invest great effort in becoming faster runners. Apart from a pure increase in the quantitative training load, a change of the running technique, e.g. transitioning from heel striking to fore- or midfoot running, can be highly effective and usually prevents kneerelated injuries.With this demo, they highlight factors to consider when determining EMS actuation phases for real-time running style correction in an outdoor scenario. During actuation the wearable applies electrical muscle stimulation (EMS) in the flight phase of a stride after having detected a heelstrike with force sensing resistors (FSR) in a sensor insole. To complement the original FootStriker lab prototype, they address the applicability in the field of the aforementioned real-time running style correction system.

In [4] proposed: Entails evaluation of patient performance in completing prescribed rehabilitation exercises, by processing movement data captured with a sensory system. Despite the essential role of re-habilitation assessment toward improved rehabilitation outcomes and reduced healthcare costs, existing approaches for computer- aided monitoring and evaluation of patient performance lack versatility, robustness, and practical relevance. In this paper, we propose a deep learning-based framework for automated assessment of the quality of physical rehabilitation exercises. The main components of the framework are metrics for quantifying movement performance, scoring functions for mapping the performance metrics into numerical scores of movement quality,and deep neural network models for regressing quality scores of input movements via supervised learning. A performance metric based on the log-likelihood of a Gaussian mixture model used for encoding low-dimensional data representation obtained with a deep auto encoder network, is proposed in the paper. Multiple deep network architectures are re purposed for the task in hand and are validated by using a data set of rehabilitation exercises. To the best of our knowledge, this is the first work that implements deep neural networks for the assessment of rehabilitation performance.a large set of examples that demonstrate the desired behavior, removing the need to specify rules explicitly. Application of these methods to medical imaging requires further assessment and validation, which used the KNN ,SVM,DTW and got 90 percent and over accuracy.

In [5] proposed: Entails evaluation of patient performance in completing prescribed rehabilitation exercises, by processing movement data captured with a sensory system. Despite the essential role of re-habilitation assessment toward improved rehabilitation outcomes and reduced healthcare costs, existing approaches for computer- aided monitoring and evaluation of patient performance lack versatility, robustness, and practical relevance. In this paper, we propose a deep learning-based framework for automated assessment of the quality of physical rehabilitation exercises. The main components of the framework are metrics for quantifying movement performance, scoring functions for mapping the performance metrics into numerical scores of movement quality,and deep neural network models for regressing quality scores of input movements via supervised learning. A performance metric based on the log-likelihood of a Gaussian mixture model used for encoding low-dimensional data representation obtained with a deep auto encoder network, is proposed in the paper. Multiple deep network architectures are re purposed for the task in hand and are validated by using a data set of rehabilitation exercises. To the best of our knowledge, this is the first work that implements deep neural networks for the assessment of rehabilitation performance.a large set of examples that demonstrate the desired behavior, removing the need to specify rules explicitly. Application of these methods to medical imaging requires further assessment and validation, which used the KNN ,SVM,DTW and got 90 percent and over accuracy.

In [6] proposed: In this paper, a real-time background modeling and maintenance based human motion detection and analysis in an indoor and an outdoor environments for visual surveillance system is described. The system operates on monocular gray scale video imagery from a static CCD camera. In order to detect foreground objects, first, background scene model is statistically learned using the redundancy of the pixel intensities in a training stage, even the background is not completely stationary. This redundancy information of the each pixel is separately stored in an history map shows how the pixel intensity values changes till now. Then the highest ratio of the redundancy on the pixel intensity values in the history map in the training sequence is determined to have initial background model of the scene. A background maintenance model is also proposed for preventing some kind of falsies, such as, illumination changes (the sun being blocked by clouds causing changes in brightness), or physical changes (person detection while he is getting out or passing in front of the parked car). At the background modeling and maintenance, the reliability and computational costs of the algorithm presented are comparatively discussed with several algorithms. Based on the background modeling, candidate foreground regions are detected using thresholding, noise cleaning and their boundaries extracted using morphological filters. Then for people detection, object detection and classification approach for distinguishing a person, a group of person from detected foreground objects (e.g., cars) using silhouette shape and periodic motion cues is performed. Finally, the trajectory of the people in motion and several motion parameters produced from the cyclic motion of silhouette of the object under tracking are implemented for analyzing people activities such as walking and running, in the video sequences. Experimental results on the different test image sequences demonstrate that the proposed algorithm has an encouraging real-time background modeling based human motion detection and analysis performance with relatively robust and low computational cost.

2.3 User Characteristics

The system contains two main users: the trainee who can create an account,choose the move he/she be preforming. Them he/she make the move and software will check if the move is write and wrong .if the move is performed in a wrong way the software will alert on the screen what is the wrong in the move in a specific period time . The Admin: Can edit,delete or update user movement and can get the results.

2.4 User Problem Statement

Our system aims to avoid the injury during the weight lift, detect the movements and classify it into right and wrong actions of the weight lifting. Then, correct the wrong moves as to limit and reduce the risk of joint injuries as much as possible. Pre-processing and joints extraction by static analysis. Rendering system also will compare with the data set of wrong movements clustering abnormal movements.

2.5 User Objectives

The Bodybuilders need to build and train their muscles, make them in the best form with the least chance of facing any type of injury. As any major injury could happen through the workout may lead him/her to the retirement. So the system will help a lot in solving this issue as it provides them with the best proper way to do the exercise, and detect the wrong moves then correct these moves to them and this is the most effective way to achieve success. The system will try to provide the most accurate functionality and everyone will be glad, as this will save them many problems (injuries), also reach their needed goal with the shortest period,by the help of coach Ahmed EL-kaissony the international team trainer to super vise on the data and as our client

2.6 General Constraints

-Strong processor.
-Big ram and big memory to store .
-The app will be constrained by the capacity of the database any update on the system will be applied to the app.
-sounds to tell the user is the movement is the wrong movement.
-Statics to show the progress and the history of the user .

3 Functional Requirements

3.1 Add user

Input	int,string(name , ID,email)
Output	The info of the user will be add
Description	the user can add data of the id and name and also the in-body
Preconditions	free space in the database
Post-condition	data base received the data
Dependencies	non
Priority	10/10

3.2 Login

Input	int , string (Password,Name)
Output	The user interface
Description	retrieve the user data from the database and check if the user exists
Preconditions	the user is logged-out
Post-condition	the user logged in and view of user account with ability to choose the movement
Dependencies	non
Priority	10/10

3.3 Capture video

Input	video file (Features), movement name (Type)
Output	csv file
Description	the user send the video to classifier to be analyzed using KNN SVM fast-DWT
Preconditions	Must have the kinect camera
Post-condition	video added to database
Dependencies	the video must be loaded
Priority	10/10

3.4 extract joints

Input	video file
Output	csv file with XYZ coordinates
Description	take the features from the video as points in 3D X,Y,Z
Preconditions	non
Post-condition	a file with the features is created
Dependencies	Capture video Function
Priority	10/10

3.5 Joint Data

Input	video file
Output	csv file with XYZ coordinates
Description	The points x,y,z in 3D are taken from the video as features
Preconditions	all the three dimensions should be taken correctly per ach joint
Post-condition	a file with the features and data of joints is created and existed
Dependencies	Joint data
Priority	10/10

3.6 choose movement

Input	int (type of movement)
Output	captured Video Features
Description	The user chooses which lift is to be classied before inserting the video into
Preconditions	non
Post-condition	The database is ready to receive the video and send it to the classifier
Dependencies	choosing the movement
Priority	10/10

3.7 Classification

Input	array of int
Output	classified data with right and wrong matrix
Description	KNN,csv,FAST-DTW are used to train and calculate accuracy
Preconditions	joint dimensions must be captured precisely
Post-condition	the video has been classified
Dependencies	Joint data
Priority	10/10

3.8 View progress

Input	arrays of different data types
Output	User Interface
Description	check and see the progress they made since the first exercise they have done
Preconditions	some videos must be added and found to compare between them
Post-condition	the final progress estimated and showed up
Dependencies	KNN, FastDTW and csv classification
Priority	8/10

3.9 Read features

Input	array of int
Output	array of int
Description	reads the points in the video, estimate their length and them back
Preconditions	none
Post-condition	csv file with the XYZ features
Dependencies	none
Priority	8/10

3.10 Write features

Input	array of int
Output	file with the features written
Description	write the points and features that have been extracted from read features
Preconditions	features must be read first by the read features function
Post-condition	none
Dependencies	read features
Priority	8/10

3.11 Fast DTW

Input	array of integers
Output	array of integers
Description	used to calculate the classify and calculate accuracy
Preconditions	none
Post-condition	video is classified
Dependencies	joint data, read and write features
Priority	9/10

3.12 KNN

Input	array of integers
Output	array of integers
Description	KNN classier classifies distance, to estimate the distance between points
Preconditions	none
Post-condition	video is classified
Dependencies	joint data, read and write features
Priority	9/10

3.13 CSV

Input	array of integers
Output	array of integers
Description	the data set has been written in csv file
Preconditions	A captured video
Post-condition	none
Dependencies	joint data, read and write features
Priority	10/10

3.14 Accuracy detection

Input	array of int
Output	array of int
Description	calculate accuracy and compare it to the model
Preconditions	points must be estimated
Post-condition	the video accuracy is outputted
Dependencies	Fast-DTW,KNN,SVM
Priority	9/10

-

3.15 Calculate progress

Input	array of integers
Output	accumulative data
Description	calculate and see the progress they made since the first exercise they have done
Preconditions	old data plus the new data
Post-condition	the final progress estimated and showed up new data
Dependencies	KNN, FastDTW and csv classification
Priority	8/10

3.16 Calculate Max Weight

Input	Int (Age, Weight, height)
Output	Max weight the User should lift
Description	calculate The maximum weight the user can lift without causing injures
Preconditions	Get weight , height , age
Post-condition	NON
Dependencies	Sign-up Function
Priority	8/10

3.17 KinectSkeleton

Input	array of int
Output	Player's skeleton
Description	This control and function is used to render a player's skeleton
Preconditions	none
Post-condition	If the ClipToBounds is set to "false", it will be allowed to overdraw it's bounds
Dependences	none
Priority	10/10

3.18 RefreshSkeleton

Input	centerPoint, jointMappings, scale, currentSkeleton
Output	Skeleton frame
Description	It will force the properties to update and trigger the control to render
Preconditions	none
Post-condition	This method should be called every skeleton frame
Dependences	none
Priority	10/10

4 Interface Requirements

This section provides full explanation of all inputs and outputs that exist in the system. It supplies also an explanation of the hardware and software. Introducing the prototypes of the user interface.

4.1 User Interfaces

The user interface is a disk-top interface and any user can access the system, to see his/her progress and the accuracy achieved by them. The video of each user supplies the right actions and the wrong actions that have been done. Also shows the correct figure of the wrong actions or movements represented on a screen. User Log-in Screen view Check performance and accuracy

Figure :[1] login with user name and the password

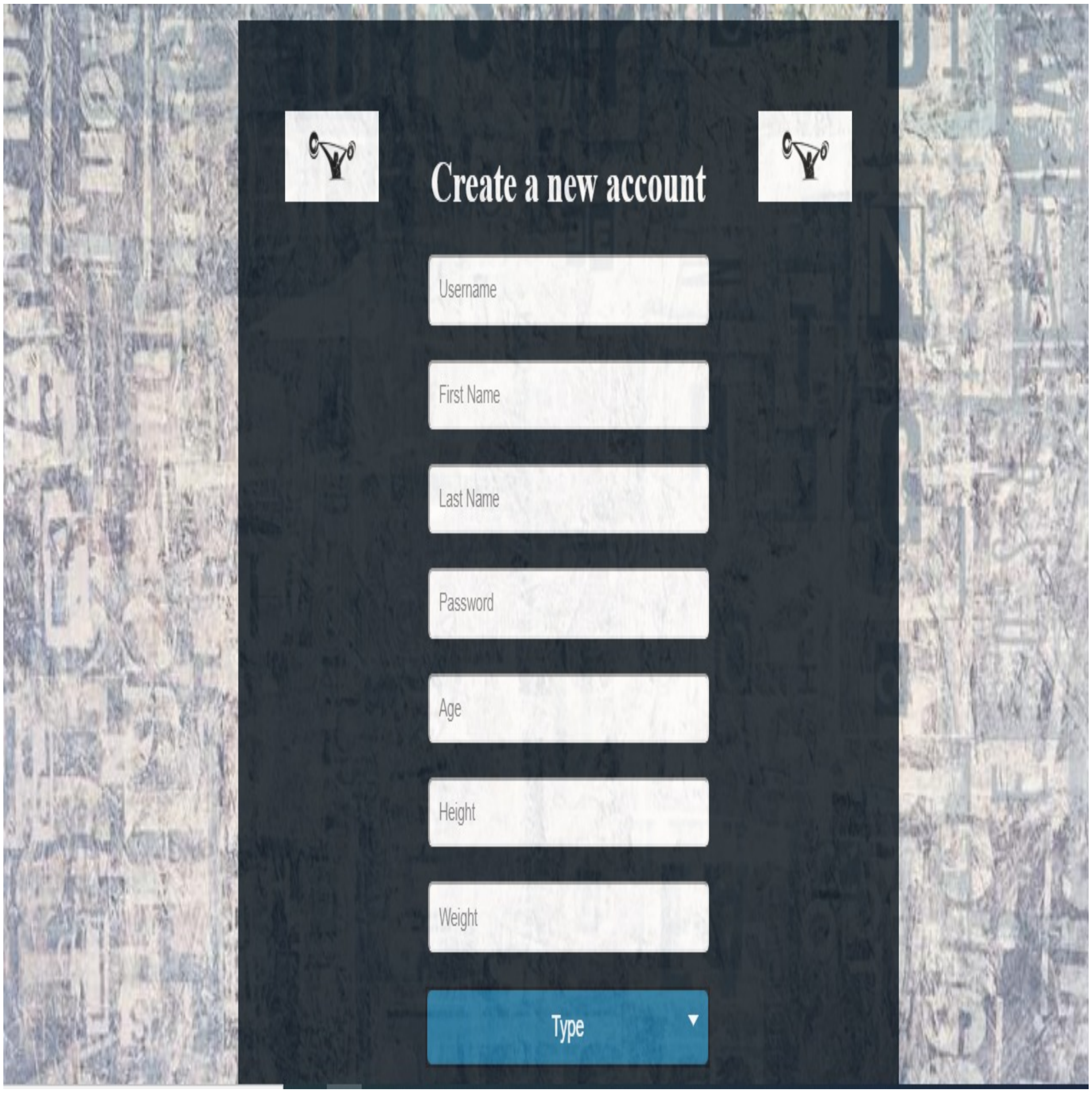


Figure :[2] signup with the user data and inbody

Figure :[3] Max Weight which will be calculated from the user in-body data

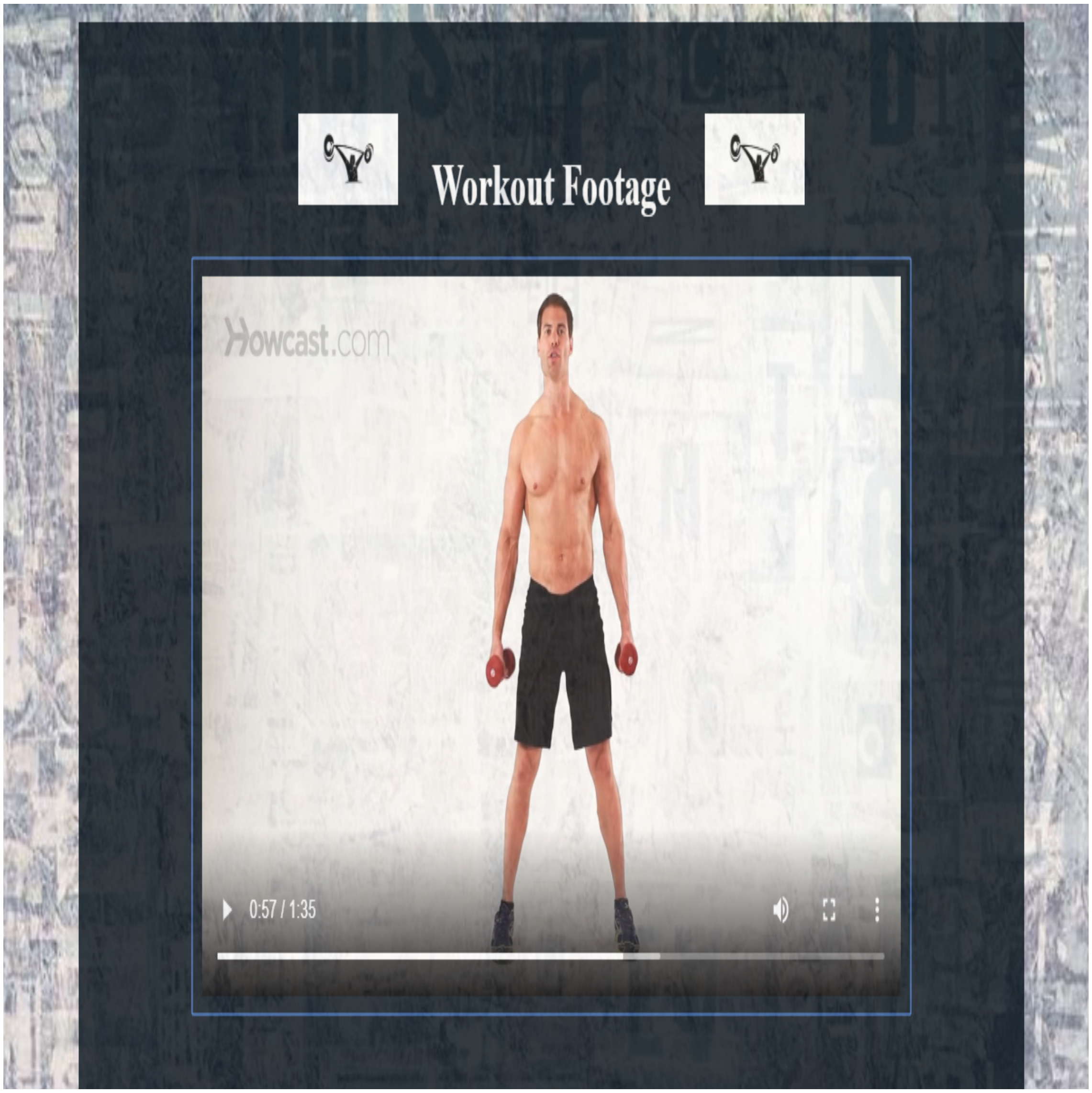


Figure :[4] choose the video

4.2 API

**Python Libraries 1.Libraries 2:numpy Libraries 3:fastdtw Libraries 4:scipy Libraries 5:cv2 Libraries 6:pandas Libraries 7:glob Libraries 8:csv Libraries 9:matplotlib Libraries **C Libraries 1;System Libraries 2:Microsoft.Kinect Libraries 3:MySql.Data Libraries 4:Collections.Generic Libraries

**Kinect API

5 Performance Requirements

The huge data set and videos exist in the system requires strong machine with big processor to run and handle it, Kinect device with its adaptor to catch the body joints movement, to classify right, wrong movements and correct the wrong ones viewed on a screen.

6 Design Constraints

6.1 Hardware Limitations

However, a strong machine does the processing of the system this system works on disk-top application.

6.2 Software Languages

Coding will be d one in Python, HTML5, bootstrap, php, and JavaScript and C .

7 non-functional requirements

7.1 Security

Each user details and information should be saved securely, correct video of movements should be accessed by the owner of it only.

7.2 Portability

The system could be accessed by any user or trainee who has user id on any platform.

7.3 Maintainability

The system could be improved by adding more movements to the application and enhancing the accuracy over time , and adding more features as in-body data calculations and other features as more details about the injuries that my happen .

7.4 Availability

The system would be available to the user, all the time and work perfectly without any drop down and undergoing repair action will be done whenever it is needed.

8 Preliminary Object-oriented Domain Analysis

8.1 Inheritance Relationships

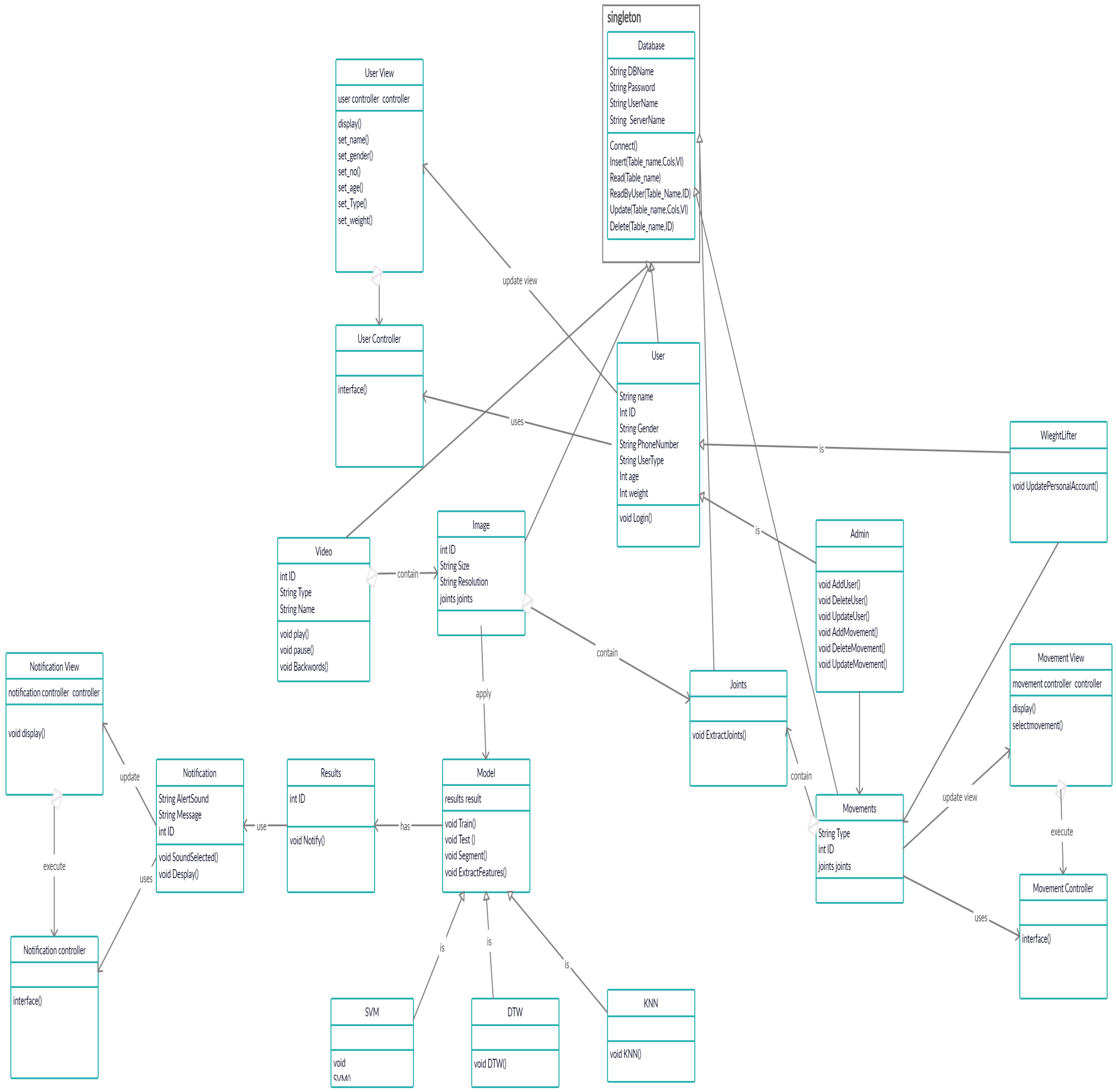


Figure 4:Class diagram

8.2 Class Description

8.2.1 User

Super classes	None
Sub classes	Admin - Weightlifter
Purpose	Contains all user details
Attributes:	name (str) - gender (str) - id (int) - usertype (str) - phoneNo (int) - age (int)
Operations	login()

8.2.2 Admin

Super classes	User
Sub classes	None
Purpose	controls the functionality of the program
Attributes:	None
Operations	UpdateUser() - AddUser() - deleteUser() - Updatemovement() - AddMovement()

8.2.3 Weight Lifter

Super classes	User
Sub classes	None
Purpose	extends user and focuses on personal account
Attributes:	None
Operations	UpdatePersonalAccount()

8.2.4 video

Super classes	None
Sub classes	Admin - Weightlifter
Purpose	Contains all video information
Attributes:	name (str) - id (int) - type (str)
Operations	play() - pause() - Backwards()

8.2.5 Image

Super classes	None
Sub classes	None
Purpose	Contains all frames and thei details
Attributes:	id (int) - size (str) - resolution (int) - joints (joints)
Operations	None

8.2.6 Movement

Super classes	None
Sub classes	None
Purpose	Contains all Movements
Attributes:	id (int) - type (str) - joints (joints)
Operations	None

8.2.7 Joint

Super classes	None
Sub classes	None
Purpose	Contains Joints extracted from user
Attributes: None	
Operations	ExtractedJoints()

8.2.8 Model

Super classes	None
Sub classes	SVM - KNN - DTW
Purpose	Contains all functions used in the algorithm
Attributes:	result (result)
Operations	train() - test() - segment() - ExtractFeatures()

8.2.9 results

Super classes	None
Sub classes	None
Purpose	Contains the classifier results
Attributes:	id (int)
Operations	notify()

9 Database Tables

10 Operational Scenarios

10.1 User

10.1.1 Data

After log in the user can show his / her information history

10.1.2 Start capture

After the user start the video capture he will do the movement due to specific time then the app will correct the movement if it is wrong and the kind of the injury that could happen and show the accuracy weather it is right or wrong.

10.1.3 The right movement

This will show the movement that the app performed in the right way so the user could learn it before using the app

10.2 Admin scenarios

10.2.1 Curd

The admin could view ,create ,update or delete the movement

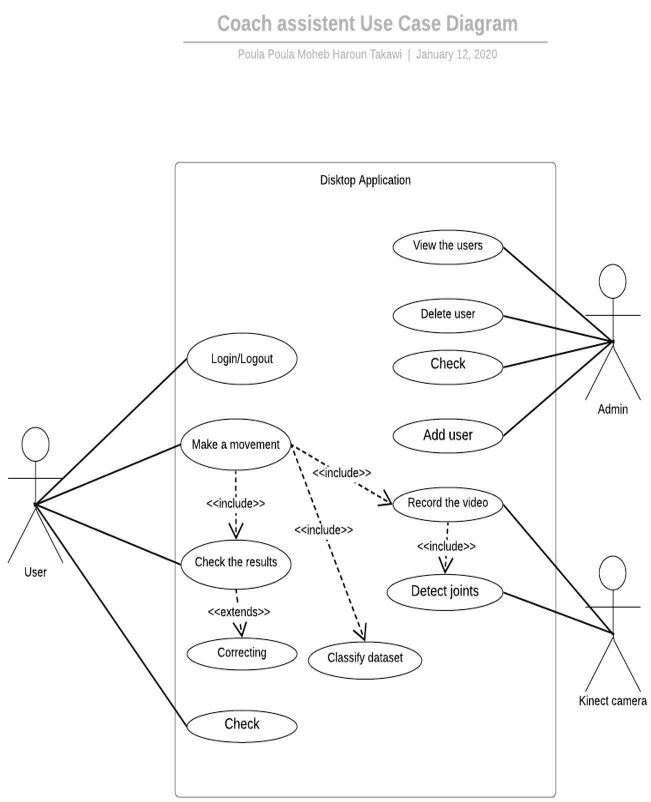
10.2.2 Update video

The admin could add new movements and new tutorials

10.2.3 Following updates

He will follow the updates and the comments for each user on their accuracy over time.

10.3 Use case diagram



10.4 System scenarios

PROJECT PHASE	STARTING	ENDING
RECIVING PROPOSALS AND IDEAS FROM DR'S AND STUDENTS	1 July 2019	15 July 2019
ANNOUNCE PROPOSALS FOR STUDENTS	16 July 2019	22 July 2019
LECTURE PRESENTATION SKILLS	1st week of classes 2019	
REGISTER STUDENTS TO PROJECTS	End of July 2019	
LECTURE WRITING PAPER SKILLS	Second week of September 2019	
1- PROPOSAL EVALUATION	First week in October 2019	
SUBMITTING CONTRIBUTION OR SURVEY PAPER	First Semester	
2- SRS EVALUATION	Second week of December 2019	
3- SDD EVALUATION	Third week of February 2020	
4- PROTOTYPE EVALUATION	3 days after Midterm exam	
LECTURE WRITING FINAL THESIS	After Spring Break	
DELIVERYING 8 PAGES CONTRIBUTION PAPER	Second Semester	
5- TECHNICAL EVALUATION	1st week of May 2020	
LECTURE WRITING CV	Beginning of May 2020	
6- FINAL THESIS	Last 10 days in June 2020	
7- CERMONEY (OOA)	24 June 2020	

11 Preliminary Budget Adjusted

The kinect camera: 3500 EGP.

The server: 350 EGP/month

12 Appendices

Reference

References

[1] Ebert, Kiermeier, Marouane Linnhoff-Popien *"SensX: About sensing and assessment of complex human motion"*. 14th IEEE International Conference on Networking, Sensing and Control (ICNSC), May 16th-18th, 2017, Calabria Italy

[2] Patty Wellborn *"UBC engineers advance the capability of wearable tech"*. The Journal of Sensors and Actuators A: Physical. 2018

[3] Wiehr, Kosmalla, Daiber Krüger *"FootStriker Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services"*. ACM New York, NY, USA ©2017

[4] Liao, Y., A. Vakanski, M. Xian *"A Deep Learning Framework for Assessing Physical Rehabilitation Exercises"*. University of Idaho, USA, Jan 29th-30th, 2019

[5] Liao, Y., A. Vakanski, M. Xian *"A Deep Learning Framework for Assessing Physical Rehabilitation Exercises"*. University of Idaho, USA, Jan 29th-30th, 2019

[6] Varun Gulshan *"Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs"*. Jama, November 29, 2016.